Represention, Use, and Acquisition of Affordances in Cognitive Systems

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Abstract

We review the psychological notion of *affordances* and examine it anew from a cognitive systems perspective. We distinguish between environmental affordances and their internal representation, choosing to focus on the latter. We consider issues that arise in representing mental affordances, using them to understand and generate plans, and learning them from experience. In each case, we present theoretical claims that, together, form an incipient theory of affordance in cognitive systems. We close by noting related research and proposing directions for future work in this arena.

1 Introduction and Background

Intelligent agents, both human and artificial, often operate in the context of an external environment and interact with entities therein. The agent can interact effectively with these objects in some ways but not others. For instance, depending on its manipulators, an agent will be able to grasp, lift, or throw some items but not different ones. Similarly, it can sit or recline on some objects but not others. Gibson (1977) referred to such relationships as *affordances*, a term that has been widely adopted in perceptual psychology, human-computer interaction, and, more recently, AI and robotics.

Gibson viewed affordances as existing in the environment, but others have used the term, rather differently, to refer to internalized models of these relations. For example, Vera and Simon (1993) have proposed that they are encoded as symbol structures which the agent can use to guide its decision making. They mapped affordances onto both the condition sides of production rules and onto perceptual chunks to which they refer. More recently, Sahin et al. (2007) and Zech et al. (2017) have reviewed different formalizations in robotics, focusing on relations between agents and the environment. We will incorporate ideas from each of these earlier efforts in our own analysis.

In this paper we present a high-level theory of affordances that makes commitments about a number of key issues. Like Vera and Simon, we focus on internal representations of affordances that describe an agent's ability for action. However, we move beyond their treatment to make more specific statements about the role of affordances in intelligence, focusing in turn on issues of representation, performance, and learning. We propose theoretical postulates about affordances that we feel are promising, but we do not report implemented agents that incorporate these tenets or experimental evaluations of them, which we reserve for future work.

2 Representing Knowledge of Affordances

Because representation constrains both performance and learning, we should address first how an intelligent agent can encode affordances in memory and how they relate to other cognitive structures. We distinguish between grounded short-term elements, say a belief that the agent can lift a particular box, and generic long-term ones, say a predicate and associated rule that specifies the class of situations in which lifting is possible. The typical usage of 'affordance' focuses on the grounded version, but we maintain that such elements are always instances of generic structures, so the primary representational challenges concern encoding the latter.

We hypothesize two distinct forms of knowledge: *concepts* that denote classes of objects or relations among them; and *skills* that specify the conditions in which multi-step activities produce specific outcomes.[1] Skills refer to concepts when describing their conditions and effects, making the latter structures more basic than the former. This leads naturally to our first theoretical postulate:

- *Affordances are concepts that describe the class of situations and the characteristics of agents for which particular activities produce specific effects.*

In other words, they are reified predicates that link the structures of objects and the features of agents that can use those objects to achieve given ends. Affordances take the same form as other concepts, in that they specify a predicate with associated arguments and a set of conditions that describe when they hold. The key difference is that each affordance concept serves as the sole condition on a skill, indicating when the latter produces its associated effects. Conceptual memory also contains other concepts, such as ones that describe situations which result from a skill's application.

Note that we view affordances as three-way relationships among the way an object is used, structural aspects of that

[1] We have borrowed this distinction from Li, Stacuzzi, and Langley's (2012) ICARUS architecture, but it has roots in psychology.

object, and characteristics of the agent that uses it. A typical hammer has a handle with a head on one end, but it cannot be used to drive a nail or spike unless the agent is strong enough to lift and swing it. This means that a sledge hammer may afford the hammering activity for some agents but not others. Some conditions in an affordance concept will be qualitative, but others will specify numeric relations, such as whether a tool's weight is less than what the agent can lift.

We also postulate that many affordances are matters of degree. Some handles are easier for a given agent to grasp than others, while some ladders are easier for that agent to climb. This suggests that logical definitions of concepts, often assumed in AI, are insufficient. Instead, we propose that:

- *Affordances are graded concepts that match situations to greater or lesser degrees.*

For instance, a hammer may be more or less usable by a person depending on the difference between its weight and what he can lift, among other factors. Probabilistic categories are one way to support graded behavior, but any approach that measures distance from a prototype or central tendency will suffice. Most work in this tradition has assumed attribute-value notations, but one can also define relational concepts that match to different degrees (e.g., Choi 2010).

Finally, treating affordances as reified conceptual predicates suggests another representational characteristic that, we hypothesize, is especially important for describing extended activities that involve multiple steps:

- *Complex affordances are decomposable into elements that denote different aspects of usability.*

For example, a tool has a hammering affordance when an agent can grasp its handle, lift it upward, and propel its flat head against the target. We can view each of these elements as a distinct 'subaffordance' that must hold, for a given agent and to a reasonable degree, to let the agent use a tool for its intended function. A hammer may be light enough for a person to lift, but it will not drive home a nail if its handle is so slippery that it flies out of his grasp or if its head is so narrow that it misses the target.

3 Using Knowledge of Affordances

Humans and other intelligent agents engage in two broad classes of knowledge-based cognition. One involves interpreting situations and events in the environment, in some cases the activities of other agents. For instance, we may observe someone stacking some boxes but appear to have difficulty lifting one that is too heavy. The simplest variant is intention recognition, which assigns an agent's behavior to some known category, such as picking up a hammer or stacking a box. A more complex version, plan understanding (e.g., Meadows et al. 2014), infers an agent's multi-step plan, including goals it aims to achieve. Our next claim involves two facets of this performance task:

- *Affordances enable both proposal of hypotheses during plan understanding and their evaluation.*

To clarify hypothesis creation, suppose that we observe someone holding a nail and reaching in the direction of two objects, a hatchet and a screwdriver. The hatchet's structure, specifically its handle and the flat side of its head, can be used to hammer the nail, suggesting this as a candidate intention. The latter occurs because the hatchet's description, obtained through perception and inference, matches the affordance conditions associated with hammering a nail. The screwdriver does not lend itself structurally to this activity, so it would not produce a comparable hypothesis.

The graded nature of affordances helps during evaluation of candidate explanations. Given a set of observations, some intentions and plans will be more plausible than others. For example, suppose we observe someone in a room picking up a shoe that has a flat heel. We might hypothesize that he plans to put the object on his foot or that he plans to use it to hammer a nail. The shoe can be used for both activities, but it matches the affordance concept for placing on a foot much better than it does the one for hammering. We can use this degree of match in our evaluation of the two hypotheses and conclude that the first alternative is more plausible.

The second performance task concerns generating activities that support one's goals. As before, the simplest cases involve selection of primitive actions, such as grasping a glass or lifting a held box. More complicated variants involve chaining sequences of actions into multi-step plans to achieve the agent's goals. This suggests another tenet:

- *Affordances aid both the proposal of actions during plan generation and their evaluation.*

For instance, suppose we want a nail embedded in a wall and we have two tools, a hatchet and a screwdriver. We might use means-ends analysis to propose a hammering activity that achieves the goal and then realize the hatchet, held in a particular orientation, satisfies the affordance concept for hammering, but the screwdriver does not. Or we might use forward chaining to identify which affordances match the current situation, retrieve their associated activities, and consider the resulting states. Hammering the nail with the reversed hatchet is an applicable action that achieves the goal, but no screwdriver-related activities are applicable. If the nail were a screw, the situation would be inverted.

Affordances can also influence evaluation of candidate intentions during the planning process. Suppose, again, that we want a nail embedded in the wall, and that we have generated two possible intentions: hammering the nail with a reversed hatchet and hammering it with a shoe. Both satisfy the relational conditions of the graded affordance for hammering, but the hatchet would match its specification better than the shoe. The reasons involve both the relative abilities for grasping the two tools and their capacities for driving the nail into the wall even when they are held firmly.

4 Acquiring Knowledge of Affordances

Now that we have discussed the representation and use of internal affordances, we can turn briefly to their acquistion from experience. Recall that affordance concepts describe the conditions under which an activity has a particular effect for an agent. The AI community has pursued two different approaches to learning about agents' activities that suggest a final theoretical postulate:

- *Primitive affordances are learned inductively whereas complex affordances are learned analytically.*

When an agent first interacts with a new object or situation, it has little knowledge on which to build. In response, learning the conditions under which an action will have desired effects – the affordance concept – is primarily empirical. For example, this can occur by attempting to grasp different objects, with induction comparing configurations of successful and unsuccesful cases (e.g., Shen and Simon 1989).

In contrast, acquisition of complex affordances occurs in the presence of existing components, enabling use of analytic methods like those used to determine conditions on macro-operators (Iba 1989). This involves composing the conditions of actions not satisfied by the effects of those that occur before them. For instance, if we have affordance concepts for grasping a hammer's handle, lifting it, and hitting a nail with its head, then each of these would appear as components of a complex affordance for hammering a nail. Interactions among these elements may require inductive refinement, but creation of an initial concept can occur analytically based on a single training case. Li et al. (2012) have adapted this compositional method to acquire definitions for new conceptual predicates, in some cases recursive ones, that serve as conditions on learned hierarchical skillls.

5 Related Research

Recent years have seen growing interest in internalized affordances within the AI and robotics communities. Horton, Chakraborty, and St. Amant (2012) review many of these efforts, which often use visual processing to classify objects as appropriate for actions. Sahin et al. (2007) and Zech et al. (2017) also offer insightful surveys of computational research on the topic. We should examine how our theoretical claims relate to the growing body of work in this area.

- *Affordances are concepts that map relations between situations and agents on the effects of actions.*

A review of the literature reveals that some aspects of this statement are widely accepted but not others. Treatments of affordances have always involved mapping objects or situations onto action relevance, and many efforts to learn such mappings produce conceptual descriptions or classifiers. However, the notion that affordances involve *interactions* between features of agents and features of objects has been much less common. Stoffregen (2003) provides an early and clear statement of this claim, but his treatment was informal and, to our knowledge, AI and robotics papers have only rarely incorporated his insight. We maintain that this important idea deserves more attention in the computational literature than it has received.

- *Affordances are graded concepts that match situations to greater or lesser degrees.*

Prior researchers have not discussed this idea directly. For instance, Sarathy and Scheutz (2016) describe an approach that uses probabilistic rules to infer affordances of objects for actions. Their framework shares our assumption that affordances are reified concepts, but not that these mental structures are graded. Zech et al. (2017) consider dynamic affordances that vary with changing properties of objects, but they remain Boolean in each case. They also suggest that agents choose among objects based on appropriateness to a given outcome, but stop short of proposing degrees of affordance. Of course, probabilistic approaches can predict how features of the agent and situation affect an action's chance of success, but graded affordances can also encode the time, effort, and difficulty of achieving an objective. Thus, this claim seems like an important contribution to the literature.

- *Complex affordances are decomposable into elements that denote different aspects of usability.*

This idea appears in a few places but has not been explored in detail. Zech et al. review a few papers that discuss a hierarchy of affordances, including Ellis and Tucker's (2000) experimental studies of 'micro-affordances' as 'potentiated components' of higher-level activities (e.g., turning a wrist while reaching for an object). However, computational researchers have generally focused on a single level of analysis. Therefore, the decomposition of complex affordances into simpler elements, and the compositional semantics it requires, is a notion that merits substantially more effort than the community has given it to date.

- *Affordances enable the proposal and evaluation of hypotheses during plan understanding.*

This theoretical tenet is both uncontroversial and supported in the literature, although few publications state it in these terms. For instance, Sindlar and Meyer (2010) report a system that uses logical reasoning about affordances to generate hypotheses about a BDI agent's intentions in a video game, but also uses numeric scores to evaluate them. In contrast, Freedman, Jung, and Zilberstein (2015) describe a probabilistic approach that ranks all candidate activities, using information about tool affordances for evaluation but not hypothesis generation. We encourage researchers who work in this area to be more explicit about the ways in which affordances guide their systems' decision making.

- *Affordances aid the proposal and evaluation of actions during plan generation.*

This postulate is also supported by publications in the area. One example comes from Ugur, Oztop, and Sahin (2011), who use learned object affordances during planning to propose candidate actions whose conditions match the current state, but not to evaluate them. In contrast, Boularias et al. (2015) use information about affordances, acquired by reinforcement learning, to evaluate alternative actions by comparing the values expected from their application.

- *Primitive affordances are learned inductively whereas complex affordances are learned analytically.*

Nearly all computational research in this arena has focused on acquiring primitive affordances and has relied exclusively on inductive methods, which is consistent with the first half of our claim. For instance, Kjellström, Romero, and Kragić (2010) describe a statistical approach to learning primitive affordances from observation for use in activity recognition, whereas Ugur et al. (2011) learn action models from exploration that map continuous features of objects to effect categories. Similarly, Boularias et al. (2015) report a system that estimates the expected values of actions in different situations, which they view as affordances, from delayed rewards. More interesting is recent work by Sridharan, Meadows, and Gomez (2017) that learns primitive affordances inductively and then combines them analytically into composite affordances on finding that sequences of actions achieve the agent's goals. However, this is the only work we have found that addresses the second half of our final tenet.

In summary, a number of theoretical claims about affordances appear to be novel, while others have received little attention. Taken together, they offer a new perspective that can drive work on embodied agents in interesting directions.

6 Concluding Remarks

In the preceding pages, we presented an account of affordances in intelligent systems. Our theory postulated these structures are reified concepts that specify when skills have particular effects for given agents, that allow graded membership, and that can be composed from more basic affordances. An intelligent system can use such structures to hypothesize and evaluate candidate plans that help understand others' behavior and achieve its own goals. Finally, such an agent can acquire affordance concepts from experience through a mixture of inductive and analytic learning mechanisms. We saw that others have explored some of these ideas, but that some appear novel, and there is no existing account of affordances that combines them into a unified theory.

In future research, we should incorporate these ideas into an implemented system, ideally an existing agent architecture that makes assumptions which are largely consistent with the new postulates (e.g., Li et al. 2012). We should also demonstrate the extended architecture on scenarios that illustrate the representation, use, and acquisition of graded, composite affordances for agents with different abilities. Finally, we should carry out experiments that test the benefits of affordance-driven processing over alternative approaches to intelligent systems. If studies reveal that this leads to better explanations, more effective plans, and reduced search, they will serve as evidence that supports the theory.

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